Toward a Meta-Framework for Conducting Mixed Methods Representation Analyses to Optimize Meta-Inferences

Julie A. Corrigan
Concordia University, Montreal, Julie.Corrigan@uottawa.ca

Anthony J. Onwuegbuzie
University of Cambridge, United Kingdom University of Johannesburg, South Africa,
tonyonwuegbuzie@aol.com

Toward a Meta-Framework for Conducting Mixed Methods Representation Analyses to Optimize Meta-Inferences

Abstract

The purpose of this article is to propose a meta-framework for conducting what we term *mixed methods representation analyses* (MMRA). We define MMRA as the appropriate selection of sampling design (i.e., the sampling frame [random] or sampling boundary [purposive]; sampling combination, comprising the mixing dimension [partial/fully], time dimension [concurrent/sequential], emphasis dimension [dominant/equal status], and relationship among/between samples [identical/parallel/nested/multilevel]; sample size; and number of sampling units [e.g., of people, cases, words, texts, observations, events, incidents, activities, experiences, or any other object of study]) in order to obtain representation and concomitantly meta-inferences consistent with the study's generalization goal(s). Thus, the goal of conducting MMRA is to attain representation and interpretive consistency in order to enhance the rigor of mixed methods research studies.

Keywords

Mixed Methods, Sampling, Saturation, Power Analysis, Representation

Creative Commons License

Toward a Meta-Framework for Conducting Mixed Methods Representation Analyses to Optimize Meta-Inferences

Julie A. Corrigan
Concordia University, Montréal, Québec, Canada

Anthony J. Onwuegbuzie
University of Cambridge, United Kingdom
University of Johannesburg, South Africa

The purpose of this article is to propose a meta-framework for conducting what we term mixed methods representation analyses (MMRA). We define MMRA as the appropriate selection of sampling design (i.e., the sampling frame [random] or sampling boundary [purposive]; sampling combination, comprising the mixing dimension [partial/fully], time dimension [concurrent/sequential], emphasis dimension [dominant/equal status], and relationship among/between samples [identical/parallel/nested/multilevel]; sample size; and number of sampling units [e.g., of people, cases, words, texts, observations, events, incidents, activities, experiences, or any other object of study]) in order to obtain representation and concomitantly meta-inferences consistent with the study's generalization goal(s). Thus, the goal of conducting MMRA is to attain representation and interpretive consistency in order to enhance the rigor of mixed methods research studies. Keywords: Mixed Methods, Sampling, Saturation, Power Analysis, Representation

As mixed methods research (MMR) prepares to leave its "adolescence" (Teddlie & Tashakkori, 2003, p. 3) and to enter young adulthood, there is a growing need for *quality standards* (Tashakkori & Teddlie, 2010a) to ensure that mixed methods researchers can secure a place at the methodological table (Collins, Onwuegbuzie, & Johnson, 2012). For example, mixed methods researchers were omitted from the invitation list when the American Educational Research Association (AERA) issued standards in 2006, and again in 2009, for reporting on empirical social science and humanities-oriented research in AERA publications (American Educational Research Association, 2006, 2009). Noticeably absent from these standards were any guidelines for mixed methods researchers. If we as mixed methods researchers wish to be taken seriously, we will need to develop fully our identity and take responsibility for developing our own guidelines before we can launch into methodological adulthood. Quality standards for MMR are beginning to accrue, especially with regards to the legitimation of MMR studies (Greene, 2007; O'Cathain, 2010; Onwuegbuzie & Johnson, 2006). Although these works provide important and necessary contributions to the development of general guidelines for mixed methods researchers, specific guidelines also are needed.

In terms of specific guidelines, one area where there is a particular paucity of information is with regards to mixed methods sampling. The *SAGE Handbook of Mixed Methods in Social Science & Behavioural Research* (Tashakkori & Teddlie, 2010b), for example, devoted only one (Collins, 2010) of its 31 chapters to the topic of sampling. *The Journal of Mixed Methods Research* has published a mere five (1.89%) out of 264 articles with sampling as the central topic between its inception in 2007 and the second issue of 2020. Further, a search of three databases (i.e., ProQuest Social Sciences, Scholar's Portal, and ERIC

[Educational Resource Information Center]) revealed only six additional articles. This is despite the fact that making correct sampling decisions is central to conducting rigorous MMR. For example, too small a sample size in the quantitative phase of a mixed methods research study will result in insufficient statistical power to determine the relationship between the independent variable and the dependent variable (J. Cohen, 1988). Too few sampling units (e.g., number of words from an interviewee, number of participants, number and length of interviews or focus groups, number of observations made) in the qualitative phase could lead to insufficient data to reach saturation (Guest, Bunce, & Johnson, 2006; Guest, Namey, & Mckenna, 2017; Namey, Guest, Mckenna, & Chen, 2016). Saturation can be operationalized as "[t]he point in data collection and analysis when new information produces little or no change to the codebook" (Guest et al., 2006, p. 65). This can be further broken down into informational redundancy (i.e., the point at which "sampling additional cases does not provide any new information"; Collins, 2010, pp. 360-361), data saturation (i.e., when information occurs so repeatedly that the researcher can anticipate it and whereby the collection of more data appears to have no additional interpretive worth (Sandelowski, 2008); and theoretical saturation (i.e., the point at which additional sampling provides no new thematic categories and that the emergent theory is adequately developed to fit any future data collected; Glaser & Strauss, 1967; Sandelowski, 2008).

As of yet, there is no bilingual term (Tashakkori & Teddlie, 2003) to denote both power (a term used by quantitative researchers) and saturation (a term used by qualitative researchers). Thus, we propose the use of the term *representation* for MMR. In fact, this term already is in use by mixed methods researchers in referring to the challenge of capturing (i.e., representing) the "lived experiences using text in general and words and numbers in particular" (Onwuegbuzie & Johnson, 2006, p. 52). We wish to use this notion of representation and to expand upon it to emphasize that as mixed methods researchers, not only do we have to represent lived experiences using numbers and words, but also we must simultaneously strive for the appropriate balance of quantitative power and qualitative saturation. Increasing one—in the real world where resources for conducting research are limited—comes at the expense of the other. We will discuss this in more detail later, but for now, suffice it to say that just as achieving power is essential to rigorous quantitative research and likewise saturation to qualitative research, representation is essential to rigorous MMR.

Key to achieving representation is making effective sampling decisions (how can the appropriate balance of power and saturation be achieved otherwise?). In mixed methods research studies, inappropriate sampling decisions are particularly problematic in sequential designs because sampling errors in the first phase are carried forward to the next phase. However, this is also an issue across all mixed methods research studies because the goal of MMR is the eventual integration of inferences from the quantitative and qualitative phases into meta-inferences (Tashakkori & Teddlie, 2003). Regardless of their purpose for mixing methods, researchers are struggling to make effective sampling decisions and, subsequently, to make appropriate inferences. Their struggle was shown in a study conducted by Collins, Onwuegbuzie, and Jiao (2007), who discovered that 53.7% of mixed methods research studies ($N = 121$) in social and health science research contained unwarranted generalizations.

Due to a dearth of literature on this topic, the importance of mixed methods sampling designs to rigorous research, and the reported high incidence of mixed methods researchers who are struggling with this topic, the purpose of this article is to propose a meta-framework—consisting of frameworks, models, and multiple research approaches—for *mixed methods representation analyses* (MMRA). Although neither quantitative power analysis (J. Cohen, 1988) nor even qualitative power analysis (Onwuegbuzie & Leech, 2007) are novel ideas, the idea of MMRA has not previously been advanced. We define MMRA as the appropriate selection of sampling design (i.e., sampling frame [random] or sampling boundary [purposive];

sampling combination, which includes the mixing dimension [partial or fully], time dimension [concurrent or sequential], emphasis dimension [dominant or equal status], and relationship among/between samples [identical, parallel, nested, or multilevel]); sample size; and number of sampling units [of people, cases, words, texts, observations, events, incidents, activities, experiences, or any other object of study]). In addition to obtaining meta-inferences that are representative of the sample, the goal of conducting MMRA is to maintain interpretive consistency in order to enhance the rigor of mixed methods research studies. According to Collins and her colleagues (Collins, 2010; Collins et al., 2007; Onwuegbuzie & Collins, 2014, 2017), interpretive consistency is the point at which the type of generalization made is warranted, given the sampling design.

Theoretical Framework

We developed our MMRA meta-framework by drawing meta-inferences from quantitative and qualitative sampling theory. As a quantitative term, power analysis is conceptually defined as "a measure of the sensitivity of the experiment to detect a real effect of the independent variable" (Pagano, 2010, p. 268). Power analysis enables researchers to determine the minimum sample size a priori, as well as to assess post-hoc power. Reporting and interpreting effect sizes helps contextualize research results and is considered so important that an American Psychological Association Task force deemed it being "essential to good research" (Wilkinson & Task Force on Statistical Inference, 1999, p. 599).

Although quantitative power analysis has a more-or-less cemented place in the research community—albeit with some continued debate (Gorard, 2015)—qualitative power analysis is newer and arguably more controversial. Onwuegbuzie and Leech (2007) posited that qualitative power analysis (based on the conventional definition of the word *power*) represents an analysis of the ability or capacity to perform or to act effectively with respect to sampling in order to assess the appropriateness of the units sampled. These authors preempt their potential detractors who would argue that sampling is unimportant to qualitative researchers by declaring that "[s]ampling in qualitative research involves making decisions not only about which individuals to study, but also about several study parameters, including settings, contexts, locations, times, events, incidents, activities, experiences, and/or social processes" (p. 117). Unfortunately, sampling has received relatively little attention in the qualitative literature, which has led to some researchers selecting their sample sizes and number of sampling units arbitrarily and not recognizing the important role that sampling plays in attaining data saturation (Onwuegbuzie & Leech, 2007).

Sampling errors are concomitant with generalization errors. Mixed methods researchers acknowledge that there is more than one type of generalization and see generalization as a goal of *all* empirical research, not merely quantitative research. Indeed, mixed methods researchers draw upon at least six generalization goals (see Table 1): external (statistical) generalization (Onwuegbuzie, Slate, Leech, & Collins, 2009); internal (statistical) generalization (Onwuegbuzie et al., 2009); analytic (particularistic) generalization (Yin, 2009); case-to-case transfer (Miles, Huberman, & Saldaña, 2014); naturalistic generalization (Stake & Trumbull, 1982); and moderatum generalization (Williams, 2000).

Although there are those who have argued that generalization has no place in qualitative research (Guba & Lincoln, 1994), this notion represents a non sequitur when researchers truthfully reflect on the analysis process (Williams, 2000). At some point—even in a study with one participant—a researcher must distill a larger body of sampling units (e.g., words, observations, artefacts, incidents) into codes, themes, categories, meta-themes, and/or some other representative classification unit. Is this not generalization, which is defined as the act of making a "general or broad statement by inferring from specific cases" (*New Oxford*

American Dictionary, 2005)? Even when qualitative work eschews the more traditional reporting of themes—such as in rhizoanalysis where "the data have been deterritorialized and reterritorialized as vignettes" resisting "temptations to interpret and ascribe meaning" (Masny, 2011)—some generalization is arguably occurring. Because data are presented through vignettes, and these are but a limited (representative) picture of the whole story, they could be interpreted as generalizations, although not in the foundationalist sense. As declared by Williams (2000), generalization, not unlike sex for the Victorian middle classes, is happening all the time, although some researchers would be loath to admit it. Researchers' knowledge of their generalization goal facilitates sampling decisions and is one of the key elements permeating our meta-framework.

About the Authors

This article was a collaboration between Julie A. Corrigan and Anthony J. (Tony) Onwuegbuzie. Julie is an Assistant Professor of Digital Literacies at Concordia University in Montreal where she teaches courses in research methods, among others. During her doctoral studies, Julie also taught research methods courses at the University of Ottawa. Throughout her time teaching these research methods courses and conducting her own research, Julie has always found it frustrating that there were no clear guidelines regarding sampling in mixed methods research. How could she teach her students to evaluate the quality of mixed methods research studies without any sense of appropriate sampling? Further, how could she and her students know whether or not a generalization was warranted, based on the sampling decision?

Julie sought out expert advice to help her frame thinking around her own research and her teaching around sampling, and mixed methods research more generally. This led to her attending an AERA workshop in 2013 entitled "Mixed data analysis techniques: A comprehensive step-by-step approach." This is where she met Tony, who was delivering the workshop (alongside his colleague Professor Kathleen M. T. Collins).

At the time, Tony was a Professor in the Department of Educational Leadership at Sam Houston State University, where he taught doctoral-level courses in qualitative research, quantitative research, and mixed methods research, including program evaluation. Currently, he is a professor and senior research associate at the University of Cambridge. Further, he is a Distinguished Visiting Professor at the University of Johannesburg; a Honorary Professor at the University of South Africa; a Honorary Visiting Scholar at Flinders University, College of Nursing and Health Sciences; a Visiting Senior Scholar at St. John's University, New York; and a Certified Ed.D. Thesis supervisor for Laureate online Education, University of Liverpool Partnership, and an Honorary Recognised Supervisor (Online), School of Histories, Languages and Cultures, at the University of Liverpool. Over the last 15 years, he has delivered more than 200 mixed methods research workshops that include instruction in qualitative research and quantitative research, across six continents, including more than a dozen workshops at the American Educational Research Association (AERA) conference. From the moment that he started teaching mixed methods research courses in 2003 at the University of South Florida, he (who had earned a methodological Ph.D., and had been trained to teach both qualitative and quantitative research courses) has been extremely passionate about mixed methods research, resulting in him serving as President of the Mixed Methods International Research Association (MMIRA; www.mmira.org).

Since their meeting in 2013, Julie and Tony have delivered a number of conference presentations, a workshop, a webinar, and have co-authored three published works on the topic of mixed methods research.

A Meta-Framework for Conducting MMRA

Method

In order to conceptualize our meta-framework for MMRA, we systematically reviewed and synthesized extant literature. Our inclusion criteria were that the article/chapter must deal with the subject of mixed methods sampling in a substantive way and must be peer-reviewed. The following is a list of the sources that we used as well as the number of hits in parentheses that met our inclusion criteria from these respective sources: *The SAGE Handbook of Mixed Methods in Social and Behavioral Research, 2nd edition* ($n = 1$); *The Journal of Mixed Methods Research* ($n = 5$); and the following databases: ProQuest Social Sciences ($n = 4$), Scholar's Portal ($n = 5$), and ERIC (i.e., Educational Resource Information Center; $n = 5$). For our database search, we performed a keyword/subject heading search using the search string "mixed methods" AND sampl* with the limiter of peer-reviewed only. No date limit was specified. Additionally, we searched the references of these articles (i.e., snowball sampling) but did not identify any new articles. After eliminating duplicates, 11 articles were identified. Of these, 10 articles were in English, two were empirical, and eight were theoretical. In addition to our review of peer-reviewed literature, we reviewed popular MMR textbooks (L. Cohen, Manion, & Morrison, 2013; Creswell, 2009; Creswell & Plano Clark, 2011; Greene, 2007; Johnson & Christensen, 2014) and found that their coverage, in terms of the percentage of the pages covering the topic of mixed methods sampling, ranged between 0.77% and 2.19%.

Results

Figure 1 represents our attempt to illustrate the process of MMRA via our meta-framework. Expanding on the work of Onwuegbuzie and Collins (2007), who identified seven distinct steps in the mixed methods sampling process, our meta-framework sees sampling as central to all 13 stages of the MMR process as identified by Collins, Onwuegbuzie, and Sutton (2006). Thus, MMRA encompasses all stages of the research process, from determining the goal of the study to writing the research report and beginning anew with reformulating the research questions (see Table 2). We do not contend that the MMRA process is linear as our two-dimensional meta-framework might make it appear; however, we believe that the straightforwardness of our model has heuristic value. What follows is a summary (unfortunately, space constraints prevent us from presenting more) of the 13-stage MMRA process.

Stage 1: Determining the Goal of the Study

We begin with Stage 1 of the MMRA meta-framework: determining the goal of the study. Clearly articulating the goal of a study importantly helps shape the sampling design, which we define as including the sampling frame/boundary, sampling combination, sample size, and number of sampling units. Articulating the goal of the study comprises several sub-steps, including the following: identifying the researcher's philosophical and conceptual stances; determining the generalization goal; identifying the theoretical, conceptual, or practical framework; and most obviously, articulating the goal of the study (Collins et al., 2006).

Encompassed in determining the goal of the study is the process of articulating the conceptual and paradigmatic stances of the researcher, although this is often dismissed as being abstract and in no way related to concrete decisions such as sampling. Quite the contrary is

true. Consider, for example, the difference that holding an *a*-paradigmatic versus complementary strengths stance would make to a researcher's sampling combination. A researcher holding an *a*-paradigmatic stance believes that "[p]aradigms comprise philosophical assumptions and stances regarding reality, knowledge, methodology, and values that are logically independent and therefore can be mixed and matched in varied combinations" (Greene, 2007, p. 68). By comparison, a researcher holding a complementary strengths stance believes that MMR is feasible, but different methods must be kept maximally separate such that the strength of each paradigmatic position (e.g., constructivism, postpositivism) can be realized. Thus, in terms of the mixing dimension (e.g., whether the sample is partially or fully mixed), an *a*-paradigmatic researcher is free to mix partially or fully the samples from the qualitative and quantitative phases. Conversely, a researcher whose stance lies in complementary strengths must keep the samples from the qualitative and quantitative phases as separate as possible. As a second example, with regards to the time dimension, a researcher holding a complementary strengths stance would be less likely to use a sequential sampling design wherein one phase is dependent upon the other because, as stated earlier, the goal would be to keep the phases as separate as possible.

Once the philosophical and conceptual stances of the researcher have been articulated, the researcher can now present the goal of the study. Goals for conducting mixed methods research studies include predicting; adding to the knowledge base; having a personal, social, and/or organizational impact; measuring change; understanding complex phenomena; testing new ideas; generating new ideas; informing constituencies; and examining the past (Newman, Ridenour, Newman, & DeMarco, 2003). Based on the researcher's goal of the study, we advocate using Bronfenbrenner's (1979) ecological system's model to help articulate the sampling frame (e.g., random sampling) or sampling boundary (purposive sampling). Bronfenbrenner's model articulates five ecological systems within which an individual interacts. The level closest to the individual—a child, for example—is the microsystem (i.e., Level 1), which includes the institutions and groups that most directly and immediately influence the child such as family, school, and peers. Next, is the mesosystem (i.e., Level 2), which is where an individual's microsystems interact, such as between the child's parents and teacher at school. The third level is the exosystem, which involves those contexts that have an indirect, although potentially profound, effect on the child's life, such as educational reform or financial upheaval. At the outermost level, the macrosystem, are the cultural ideologies and attitudes that indirectly affect the individual. Encapsulating these levels is the chronosystem examining how individuals interact with their ecological system over time. Thus, an important first step for researchers in selecting the sampling design is to conceptualize the level of system that they wish to investigate. For example, if a researcher's goal were to have an organizational impact, say at the state or national level, then a researcher would want to conduct a study at the exosystem level. This knowledge of the ecological system level, in turn, helps to inform the level of generalization that a researcher wishes to make, which we discuss next (Onwuegbuzie & Collins, 2014, 2017),

Attaining interpretive consistency, that is, having the level of generalization goal match the level of results, is paramount to rigorous MMR. That is why determining the generalization goal is so crucial to Step 1 of the MMRA meta-framework, determining the goal of the study, and, indeed, the remainder of the study. To illustrate, take the former example of having an organizational impact at the level of the state. Here, it would be inappropriate to conduct a case study at the microsystem level (say, the child's classroom) and make external generalizations to the population of children in the state. Having an organizational impact at the level of the state would require a researcher to perform a study at the exosystem level and to make external generalizations based on some form of random sample (e.g., stratified random sampling) from the population of all children in the state. Similarly, if a researcher wanted to

learn how to improve learning for students at a particular school, it would be inappropriate to apply external generalization from the state level (although these generalizations might be consulted), particularly if this school is an outlier. Rather, it would be better to perform a study at the school level and make internal generalizations or even external generalizations, but at the level of the school (mesosystem), not the state (exosystem). Attaining interpretive consistency means having consistency between the generalization goals and all stages of the mixed methods research process, including, most importantly for this article, the sampling design. Table 1 summarizes six major types of generalization goals and recommendations from the literature with regard to sample size and number of sampling units associated with those types of generalizations, as well as the assumptions implicit in reporting these types of generalizations.

Stage 2: Formulating the Research Objectives

The process of formulating research objectives helps a researcher to determine both the emphasis dimension (i.e., dominant or equal status) and the type of sampling frame or boundary (i.e., probability or purposive sampling) of the quantitative, qualitative, or mixed phase(s) of the study (Onwuegbuzie & Collins, 2007). Johnson and Christensen (2019) have identified six mixed research objectives: exploration, description, understanding, explanation, prediction, and influence. To illustrate how formulating the research objective helps to determine the sampling design, consider a study in which the objective was to *explore* a phenomenon about which little is known, such as how a low-incidence learning disability affects the writing process among elementary school students. The research objectives of both exploration and understanding naturally are suited to a qualitative-dominant (in terms of the emphasis dimension) study using purposive sampling (in terms of the sampling boundary). However, using a small sample size with a purposeful sample is not always indicative of a qualitative-dominant study. Suppose that, to follow up on the previous example, after exploring this low-incidence learning disability and its effect on the writing process among elementary students, a researcher now had the objective of *predicting* which intervention would help to boost writing achievement among this group of students. Intervention studies are experimental designs that utilize a quantitative-dominant approach. Normally, quantitative-dominant studies optimally are associated with random sampling and a large sample size. However, for this quantitative-dominant study, the sampling would be purposeful (only students with the learning disability) and the sample size small (because the learning disability is a low-incidence one, achieving a large sample size would be impossible). Dichotomizing qualitative and quantitative phases in a MMR study in terms of small/large samples or purposeful/random sampling is unhelpful. Rather, a researcher should carefully reflect on the research objective and how this affects the sampling design instead of making assumptions.

Step 3: Determine the Research/Mixing Rationale

Determining the research or mixing rationale involves explicitly stating why the study is needed, as well as why and how the qualitative and quantitative components should be mixed. Although this might seem like an obvious component of reporting an empirical study, "[d]isturbingly, a high proportion of researchers (40%) do not make clear the rationale of their study" (Onwuegbuzie & Daniel, 2005, p. 2). With regard to mixing the qualitative and quantitative components, Collins et al. (2006) have identified empirically the following four rationales: participant enrichment, instrument fidelity, treatment integrity, and significance enhancement. Once the rationale(s) has/have been determined, the researcher is best able to select the most appropriate sampling design to optimize participant enrichment, instrument

fidelity, treatment integrity, and/or significance enhancement. Take, for example, a study with the rationale of instrument fidelity, specifically with regard to the creation of a new survey instrument. Briefly, survey development generally begins with a systematic review of the literature to identify the construct, followed by the development of survey items that are piloted via focus groups and/or by an expert panel. Later, the instrument is field tested by a much larger, randomly selected sample (see, for e.g., Onwuegbuzie, Bustamante, & Nelson, 2010). This type of study suggests a fully mixed (mixing dimension), sequential (time dimension), equal status (emphasis dimension), and multilevel (relationship among/between samples) sampling combination. As has been illustrated, determining the research and/or mixing rationale helps to clarify sampling decisions.

Step 4: Determining the Research/Mixing Purposes

Although the rationale indicates why the study is needed, the research/mixing purpose describes how the qualitative and quantitative components will be mixed in the study. By examining published research, Greene, Caracelli, and Graham (1989) inductively identified five purposes for mixing methods: triangulation, complementarity, development, initiation, and expansion. Knowledge of the research and mixing purpose helps a researcher determine the time (think dependency) dimension (i.e., sequential or concurrent) of the sampling design (Onwuegbuzie & Collins, 2007). A special note here is that the terms *sequential* and *concurrent* often are misconstrued to refer solely to the chronological order in which the phases occur; rather, these terms refer mainly to whether or not one phase is dependent on (and thus must follow, chronologically) the other phase. Thus, whether a phase happens 1 day, 1 month, or 1 year after the preceding one is irrelevant; instead, what is relevant is whether the proceeding phase was dependent on the preceding one, such as when a survey is used (quantitative phase) to identify participants for a focus group (qualitative phase). Certain research purposes naturally align better with a given timing dimension. For example, triangulation must involve the use of a concurrent design because the data extracted from one phase cannot be dependent on the data obtained from another phase; otherwise, bias is introduced into a comparison of data from these two phases. Similarly, complementarity is consistent with a concurrent design because the data from one phase are not dependent upon the other, but rather are used to elaborate, to clarify, and to enhance. Conversely, development and expansion rely on sequential designs because data from one phase inform subsequent phases.

Step 5: Determining the Research Questions

As identified by Plano Clark and Badiee (2010), MMR can be utilized to address the following types of research questions: separate research questions, general overarching mixed methods research questions, hybrid mixed methods issue research questions, mixed methods procedural/mixing research questions, combination research questions, independent research questions, dependent research questions, predetermined research questions, and emergent research questions (see Table 2). All these types of research questions delimit the sampling frame/boundary, which is important because

> choosing carefully the sampling frame (quantitative) and sampling boundary (qualitative) ensures that the sampling unit or case will generate an adequate and sufficient data source to enable the mixed researcher to formulate conclusions and interpretations in each phase of the study which then are integrated into meta-inferences. (Collins, 2010, p. 370)

For the quantitative phase, the sampling frame ideally

> predetermines the number of sampling units, preferably based on a mathematical formula, such a power analysis, and selects the units by using simple random sampling or other adaptations of simple random sampling, specifically, stratified, systematic, cluster, and two-stage or multistage. (Collins, 2010, p. 357; These elements will be discussed in detail in Stage 6)

The sampling boundary (or sampling case, as it is referred to in case study methodologies) for the qualitative phase delineates the case in terms of the "time boundary covered by the case; the relevant social group, organization, or geographic area; the type of evidence to be collected; and the priorities for data collection and analysis" (Yin, 2009, Chapter 2, Exercise 2.1, para. 1). For a mixed phase (concurrently collecting both quantitative and qualitative data), the researcher must consider both the sampling frame and boundary. Because research questions importantly guide the entire study, it is important that researchers carefully and explicitly delimit the sampling frame and/or boundary. Other principles in writing mixed methods research questions that align with the sampling design include ensuring that when the answer to one research question is dependent upon the next, a sequential design is specified in the research question. Along the same vein, research questions should be listed in the order in which they are to be studied with sequential designs (Plano Clark & Badiee, 2010).

Step 6: Selecting the Sampling Design

In MMRA, selecting the sampling design consists of the following four sub-steps: (a) setting the sampling frame/boundary, (b) selecting the sampling combination, (c) selecting the sampling size, and (d) selecting the number of sampling units. By this step in the MMRA meta-framework, many of these sampling decisions have been carefully considered concerning the research goal, objective, rationale, purpose, and research questions. Here, we describe these sub-steps further.

Setting the sampling frame/boundary. Thus far, we have defined the sampling frame as being a quantitative means of determining a sample size ideally via a mathematical formula, such as in a quantitative power analysis. Also, we have stipulated that sampling frames ideally should involve random (i.e., probabilitistic) sampling techniques, as opposed to purposive sampling techniques—although this is rarely the case in the social, behavioral, and health fields (Onwuegbuzie & Collins, 2007). At this juncture, we also wish to point out that there are multiple types of random sampling techniques, primarily the following: simple, stratified, cluster, systematic, and multi-stage. These are described further in Table 3. In terms of setting the sampling boundary, we have stipulated that a sampling boundary typically is associated with qualitative research methods and usually involves the employment of purposive sampling techniques. As with random sampling techniques, there are multiple forms of purposive sampling techniques, including the following 19: convenience, maximum variation, homogeneous, critical case, theory-based, confirming/disconfirming, snowball/chain, extreme case, typical case, intensity, politically important case, random purposeful, stratified purposeful, criterion, opportunistic, mixed purposeful, quota, multistage purposeful random, and multistage purposeful (cf. Onwuegbuzie & Collins, 2007; Table 3). For both the sampling frame and boundary, it is important for researchers to delineate clearly the inclusion/exclusion criteria (Wisdom, Cavaleri, Onwuegbuzie, & Green, 2012), namely, the rationale for what was or was not included in the sample. Clearly, the choice of sampling design is much more

complex in MMR studies than in monomethod studies, particularly because there is a multiplicative effect once purposive and random sampling techniques are combined.

Sampling combination. Setting the sampling frame/boundary is followed by selecting the sampling combination (see abstract for description). Because these terms have been hitherto described and illustrated, here we illustrate how they all work in tandem to create a MMR sampling combination. Onwuegbuzie and Collins (2007) present a helpful schema for mixed methods sampling that comprises the following sampling combinations: concurrent–identical, concurrent–parallel, concurrent–nested, concurrent–multilevel, sequential–identical, sequential–parallel, sequential–nested, and sequential–multilevel. We have already described the earlier portion of these hyphenated terms (i.e., concurrent vs. sequential) and now we will describe the latter portion. The terms identical, parallel, nested, and multilevel refer to the relationship between/among the samples, as follows:

- an *identical* relationship indicates that exactly the same sample members participate in both the qualitative and quantitative phases of the study;
- a *parallel* relationship denotes that samples for the qualitative and quantitative components of the investigation are different but are drawn from the same underlying population (e.g., elementary school students from one school in one phase and elementary school students from another school for the other phase);
- a *nested* relationship implies that the sample members selected for one component of the inquiry represent a subset of those participants chosen for the other phase of the study (e.g., focus group participants are selected from survey respondents who meet chosen criteria); and
- a *multilevel* relationship involves the use of two or more sets of samples that are obtained from different levels of the investigation (i.e., different populations). For example, whereas one phase of the study (e.g., quantitative phase) might involve the sampling of students within a high school, the other phase (e.g., qualitative) might involve the sampling of their teachers, principal, and/or parents.

Sample size and number of sampling units. The element of sampling that likely most readily comes to mind when a researcher considers sampling is attention to the sample size and/or number of sampling units, which involves both quantitative and qualitative power analyses. Attention to the sample size and number of sampling units needs to occur before, during, and after both the qualitative and quantitative phases. Qualitative power analysis importantly begins with consulting the literature in one's field or inquiry approach (e.g., case study, ethnography, grounded theory, phenomenology, experimental, causal-comparative) to ascertain the established, acceptable sample sizes. Table 4 summarizes minimum sample size recommendations for selected qualitative and quantitative research designs.

In terms of quantitative power analysis specifically, conducting the analysis a priori helps *increase* both the internal validity (i.e., ensuring that the inferential test had a sufficient sample size to detect a statistically significant finding at the desired level of α [e.g., .05], statistical power [e.g., p. 80]), and external validity (i.e., if the goal is to generalize the findings to the population from which the sample was drawn; cf. Krejecie & Morgan, 1970) of the findings, whereas conducting the analysis post hoc helps *assess* the internal validity of the findings; thus, both power analyses should be considered, although the former often is neglected (Onwuegbuzie & Leech, 2007). Because quantitative power analyses calculations can be complex, we recommend the following online resources: for a priori power analysis, G*Power (http://www.gpower.hhu.de) and for post-hoc analysis, there exist a number of online

calculators such as the one found here: http://www.surveysystem.com/sscalc.htm (also, see the power table in Krejecie & Morgan, 1970).

Even after careful quantitative and qualitative power analyses, for most research studies, time and resources inevitably must be considered when selecting the sample size and number of sampling units. However, carefully selecting the sample size and number of sampling units allows the mixed methods researcher to achieve the gold standard of power in the quantitative phase and saturation in the qualitative phase.

Step 7: Selecting the Mixed Methods Research Design

Selecting the MMR design involves the identification of the following: the level of mixing, the time orientation, and the emphasis of approaches. In terms of the level of mixing, MMR designs can either fully or partially mixed. Fully mixed designs represent the highest degree of mixing. In fully mixed designs, both qualitative and quantitative research elements are mixed within one or more components of a research study (e.g., data collection, data analysis; Leech & Onwuegbuzie, 2009). In partially mixed designs, the quantitative and qualitative phases are not mixed within or across stages. Instead, both the quantitative and qualitative elements are conducted either concurrently or sequentially in their entirety before being mixed at the data interpretation stage. Secondly, in addition to the level of mixing is the time dimension, which was previously discussed in Step 4. Thirdly comes the emphasis approach, which pertains to "whether both qualitative and quantitative phases of the study have approximately equal emphasis (i.e., equal status) with respect to addressing the research question(s), or whether one component has significantly higher priority than does the other phase (i.e., dominant status)" (Leech & Onwuegbuzie, 2009, p. 268). Leech and Onwuegbuzie (2009; see Figure 1, p. 279) present a helpful decision tree diagram to help conceptualize the various MMR design typologies, including the three dimensions (mixing, time, and emphasis) hitherto mentioned. Thus, a researcher might report nomenclature such as having used a fully mixed, sequential, dominant status design. Finally, in addition to reporting the mixed methods research design, the researcher also needs to report the designs used for each qualitative phase (e.g., ethnography, oral history, case study, grounded theory; see Onwuegbuzie & Denham, 2014, for a description of 34 qualitative research designs) and quantitative phase (e.g., descriptive, correlational, causal-comparative, quasi-experimental, experimental; see Table A.1 in Onwuegbuzie & Frels, 2016, for a description of 31 quantitative research designs).

MMR designs are inextricably connected to mixed methods sampling designs. For example, the choice of a fully mixed research design likely necessitates a larger sample size and number of sampling units because the qualitative and quantitative samples are integrated across the study, including at the level of analysis; thus, the qualitative sample must be large enough to meet the statistical assumptions required in quantitative analyses. Further, research and sampling designs are connected because different sample sizes are needed for different mixed research designs, including designs for each quantitative and qualitative phase.

Step 8: Collecting Data

Throughout the data collection process, the researcher needs to reflect on the sampling boundary and/or frame and whether further sampling needs to occur to achieve greater saturation and/or power. With respect to the qualitative phase of a MMR study, for example, the Glaserian form of grounded theory is characterized by using what Glaser and Strauss (1967) referred to as *theoretical sampling*, wherein the researcher collects and analyzes data, which, in turn, informs what data to collect next and, even more importantly, what sampling boundary to use to collect these data, in order to develop a theory as it emerges. With regard to the

quantitative phase of a MMR study, for example, a multiple baseline design—which involves the meticulous measurement of multiple individuals, characteristics, settings, or the like, both before and after a treatment such that the beginning of treatment conditions is staggered (i.e., started at different times) across individuals—involves making sampling decisions at every stage of the process. Further, for both the qualitative and quantitative components of a MMR study, due to the likelihood of participant attrition and/or non-response, it is wise to oversample.

Step 9: Analyzing Data

When analyzing data, a mixed methods researcher needs to choose analyses that are appropriate for the sample size and/or number of sampling units. Various statistical analyses require that data meet a variety of assumptions. For example, when using multiple regression analysis, independent variables (IVs) should be strongly correlated with the dependent variable, but uncorrelated with other IVs. Also, the case-to-IV ratio must be substantial; there must not be too many outliers; there must be an absence of multicollinearity and singularity; and the data set must possess normality, linearity, and homoscedasticity of residuals. These are simply a few of the ways to ensure that there are no gross violations of assumptions when performing multiple regression (Tabachnick & Fidell, 2007). Similarly, when conducting qualitative data analysis, violations occur when insufficient data are collected to achieve saturation, whether informational redundancy, data saturation, or theoretical saturation; in other words, the analysis is incomplete unless saturation is (approximately) achieved.

In MMR, the integration of samples often occurs at the analysis phase via qualitizing and/or quantitizing data. Qualitizing data is

> a common term used by mixed methods researchers to denote a process by which quantitative data are converted into data that may be analyzed qualitatively (Tashakkori & Teddlie, 1998). One way of qualitizing data is to use narrative profile formation (i.e., modal profiles, average profiles, holistic profiles, comparative profiles, normative profiles), wherein narrative descriptions are constructed from statistical data. (Collins et al., 2006, p. 84; see also Onwuegbuzie & Leech, 2019)

In the same way that quantitative data can be qualitized for further analysis, qualitative data can be quantitized. Basically, this quantitizing process occurs by assigning numbers to qualitative categories to facilitate comparison of unique data sources or even for statistical analyses including exploratory, explanatory, comparative, predictive, or confirmatory statistical analyses (Sandelowski, Volis, & Knafl, 2009).

The sample size or number of sampling units should permit the researcher to reach a reasonable saturation/representation (Teddlie & Yu, 2007)—or what we call saturation/power—trade-off. This refers to achieving the appropriate level of saturation or power in light of the goal and emphasis of one's study. Thus, a qualitative-dominant study might sacrifice statistical power in order to achieve greater saturation; conversely, a quantitative-dominant design might increase statistical power at the expense of saturation. In other words, a researcher must find the appropriate balance between depth (saturation) and breadth (power) to achieve *representation* in MMRA. In equal-status designs, power and saturation exist in dynamic tension.

Step 10: Legitimating the Data

Legitimation is the mixed methods bilingual nomenclature that connotes the quantitative term *validity* and the qualitative term *trustworthiness* (Onwuegbuzie & Johnson, 2006). In other words, legitimation is how mixed methods researchers assess the quality of a research study, its conclusions, and their uses and interpretations, as well as their intended and unintended consequences. Three areas represent potential threats to the legitimation of MMR and concomitantly, sampling: representation, integration, and legitimation.

Firstly, as has been mentioned, representation refers to "the difficulty in capturing (i.e., representing) lived experiences using text in general and words and numbers in particular" (Onwuegbuzie & Johnson, 2006, p. 52). In MMR, representation issues abound in both quantitative and qualitative sampling, as well as when these samples are integrated. In quantitative sampling, issues occur when the sample is not truly representative of the population—for example, when the sample has self-selected and not been randomly selected, as is often the case with survey respondents when the survey is voluntary. In qualitative sampling, representation issues occur when, for example, one participant dominates a focus group; this means that the sampling units—here, the focus group participants' words—are not truly representative of the participants within the sampling boundary. In MMR, representation is further complicated when words are transformed into numbers (i.e., quantitizing; Sandelowski et al., 2009; Tashakkori & Teddlie, 1998) and number into words (i.e., qualitizing; Onwuegbuzie & Leech, 2019; Tashakkori & Teddlie, 1998) in the sense that, throughout this transformation, the fidelity of the original data must be maintained.

Secondly, integration plagues MMR and sampling, more specifically. Integration refers to "the complexity involved in combining qualitative and quantitative studies either in a concurrent, sequential, conversion, parallel, or fully mixed manner" (Onwuegbuzie & Johnson, 2006, p. 53; see also Onwuegbuzie & Hitchcock, 2019). The complexity faced when combining both qualitative and quantitative samples in order to make meta-inferences is made evident through questions such as the following:

> Is it misleading to triangulate, consolidate, or compare quantitative findings and inferences stemming from a large random sample on equal grounds with qualitative data arising from a small purposive sample? How much weight should be placed on quantitative data compared to qualitative data? Are quantitatively confirmed findings more important than findings that emerge during a qualitative study component? When findings conflict, what is one to conclude? (Onwuegbuzie & Johnson, 2006, p. 54)

These are complex questions and beyond the scope of this article to cover in detail (please refer to Onwuegbuzie & Johnson, 2006 for further discussion). However, in brief, we will state that these questions deal with sample integration legitimation, which will be discussed forthwith.

A third issue facing MMR is legitimation, referring to "the difficulty in obtaining findings and/or making inferences that are credible, trustworthy, dependable, transferable, and/or confirmable, and integration" (Onwuegbuzie & Johnson, 2006, p. 52; see also Collins et al., 2012; Onwuegbuzie, Johnson, & Collins, 2011). This is such a perplexing issue that Teddlie and Tashakkori (2003) identified drawing inferences as one of the six unresolved issues and controversies in mixed research. Thankfully, mixed methods researchers have at their disposal to evaluate numerous research legitimation types, including sample integration legitimation, insider–outsider legitimation, weakness minimization legitimation, sequential legitimation, conversion legitimation, paradigmatic mixing legitimation, commensurability legitimation, multiple validities legitimation, and political legitimation (Onwuegbuzie &

Johnson, 2006). Of these, the first, sample integration legitimation, is the most pertinent to MMRA. Sample integration legitimation is defined as the "extent to which the relationship between the quantitative and qualitative sampling designs yields quality meta-inferences" (Onwuegbuzie & Johnson, 2006, p. 57). Questions such as those in the preceding paragraph can be addressed through sample integration legitimation. Put succinctly, higher quality meta-inferences can be obtained when (a) samples from differing phases are more similar than different, (b) larger and ideally random samples are used, and (c) equal status designs are used. For the rationale behind these recommendations, please consult Onwuegbuzie and Johnson (2006).

Step 11: Interpreting the Data

As stated at the onset of this article, interpretive consistency is the chief goal of MMRA. In other words, MMRA is designed to help mixed methods researchers select the most appropriate sampling design for the desired generalization goal. As was illustrated in Step 1, interpretive consistency is compromised when generalizations are made beyond or below the ecological level of research conducted in a study. Mixed methods researchers acknowledge naturalistic generalization as being part and parcel of the dissemination of research, meaning that audiences will evaluate the extent that the findings are generalizable based on their personal or vicarious experiences (Stake & Trumbull, 1982). However, the degree to which the audience and the author have a more similar interpretation can be enhanced by ensuring that the significance of all findings—whether statistical, practical, clinical, or economic (Leech & Onwuegbuzie, 2004)—is clearly stated. This is the case regardless of the sample size and the generalization goal. In particular, when some form of external generalization is involved, a post-hoc power analysis for all statistically non-significant findings should be reported (Onwuegbuzie & Leech, 2004). For qualitative research, the significance (i.e., the meaning) of all findings should be interpreted by juxtaposing the empirical results of the study with the corpus of literature from the field. Finally, the appropriateness of the generalizations should be justified by reporting the results of the MMRA.

Step 12: Writing the Research Report

When writing the research report, attention should be given to the rigorous sampling design considerations made through MMRA, which ultimately justify the study's generalizability. All sampling decisions made during the MMRA process should be thoroughly documented, leaving a detailed audit trail of the sampling decisions and the justifications behind them. Also, specifically, the mixed methods researcher should report the sampling frame/boundary, sampling design, effect sizes, and whether or not the data achieved saturation and/or power.

Step 13: Reformulating the Research Question(s)

The final step in the MMRA meta-framework is to reformulate the research question(s) and to begin the research process anew. This might prompt the mixed methods researcher to ask, 'How could this study be designed using a different sample frame/boundary or sampling design to enhance one or more of the generalization goals?'

Conclusions

As MMR reaches its methodological adulthood, more explicit and specific guidelines will be needed to advise researchers regarding important issues such as sampling. Failure to align sampling decisions with the research goal, objective, rationale, purpose, research questions, and research design—as well as the subsequent data analyses, legitimation, and interpretation—can lead to challenges of representation, legitimation, integration, and politics (Onwuegbuzie & Johnson, 2006). The additive or multiplicative effects of inappropriate sampling designs adversely affect the data collected such that the legitimacy of meta-inferences (sample integration legitimation) is compromised. This is not simply conjecture, but, as previously mentioned, has been empirically demonstrated (Collins et al., 2007). Therefore, the time has come for MMRA.

References

American Educational Research Association. (2006). Standards for reporting on empirical social science research in AERA Publications. *Educational Researcher*, *35*, 33-40. doi:10.3102/0013189X035006033

American Educational Research Association. (2009). Standards for reporting on humanities-oriented research in AERA Publications. *Educational Researcher*, *38*, 481-486. doi:10.3102/0013189X09341833

Bronfenbrenner, U. (1979). *The ecology of human development: Experiments by nature and design*. Cambridge, MA: Harvard University Press.

Cohen, J. (1988). *Statistical power analysis for the behavioural sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Cohen, L., Manion, L., & Morrison, K. (2013). *Research methods in education* (7th ed.). New York, NY: Routledge/Taylor & Francis Group.

Collins, K. M. T. (2010). Advanced sampling designs in mixed research. In A. Tashakkori & C. Teddlie (Eds.), *SAGE handbook of mixed methods in social and behavioral research* (2nd ed., pp. 353-377). Thousand Oaks, CA: Sage.

Collins, K. M. T., Onwuegbuzie, A. J., & Jiao, Q. G. (2007). A mixed methods investigation of mixed methods sampling designs in social and health science research. *Journal of Mixed Methods Research*, *1*, 267-294. doi:10.1177/1558689807299526

Collins, K. M. T., Onwuegbuzie, A. J., & Johnson, R. B. (2012). Securing a place at the table: A review and extension of legitimation criteria for the conduct of mixed research. *American Behavioral Scientist*, *56*, 849-865. doi:10.1177/0002764211433799

Collins, K. M. T., Onwuegbuzie, A. J., & Sutton, I. L. (2006). A model incorporating the rationale and purpose for conducting mixed-methods research in special education and beyond. *Learning Disabilities: A Contemporary Journal*, *4*, 67-100.

Creswell, J. W. (2009). *Research design: Qualitative, quantitative, and mixed methods approaches* (3rd ed.). Thousand Oaks, CA: Sage.

Creswell, J. W., & Plano Clark, V. L. (2011). *Designing and conducting mixed methods research* (Kindle 2nd.). Thousand Oaks, CA: Sage.

Glaser, B. G., & Strauss, A. L. (1967). *The discovery of grounded theory: Strategies for qualitative research*. Chicago, IL: Aldine.

Gorard, S. (2015). Introducing the mean absolute deviation "effect" size. *International Journal of Research & Method in Education*, *38*, 105-114. doi:10.1080/1743727X.2014.920810

Greene, J. C. (2007). *Mixed methods in social inquiry*. San Francisco, CA: Jossey-Bass.

Greene, J. C., Caracelli, V. J., & Graham, W. F. (1989). Toward a conceptual framework for mixed-method evaluation designs. *Educational Evaluation and Policy Analysis*, *11*,

255-274. doi:10.3102/01623737011003255

Guba, E. G., & Lincoln, Y. S. (1994). Competing paradigms in qualitative research. In N. K. Denzin & Y. S. Lincoln (Eds.), *The handbook of qualitative research* (pp. 105-117). Thousand Oaks, CA: Sage.

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough?: An experiment with data saturation and variability. *Field Methods*, *18*, 59-82. doi:10.1177/1525822X05279903

Guest, G., Namey, E., & Mckenna, K. (2017). How many focus groups are enough? Building an evidence base for nonprobability sample sizes. *Field Methods, 29*, 3-22. doi:10.1177/1525822X16639015

Johnson, R. B., & Christensen, L. (2019). *Educational research: Quantitative, qualitative, and mixed approaches* (7th ed.). Thousand Oaks, CA: Sage.

Krejecie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement*, *30*, 607-610.

Leech, N. L., & Onwuegbuzie, A. J. (2004). A proposed fourth measure of significance: The role of economic significance in educational research. *Evaluation and Research in Education*, *18*, 179-198. doi:10.1080/09500790408668317

Leech, N. L., & Onwuegbuzie, A. J. (2009). A typology of mixed methods research designs. *Quality and Quantity*, *43*, 265-275. doi:10.1007/s11135-007-9105-3

Masny, D. (2011). Multiple literacies theory: Exploring futures. *Policy Futures in Education*, *9*, 494-504. doi:10.2304/pfie.2011.9.4.494

Miles, M. B., Huberman, A. M., & Saldaña, J. (2014). *Qualitative data analysis: A methods sourcebook* (3rd ed.). Thousand Oaks, CA: Sage.

Namey, E., Guest, G., Mckenna, K., & Chen, M. (2016). Evaluating bang for the buck: A cost-effectiveness comparison between individual interviews and focus groups based on thematic saturation levels. *American Journal of Evaluation*, *37*, 425-440. doi:10.1177/1098214016630406

New Oxford American Dictionary. (2005) (online.). New York, NY: Oxford University Press.

Newman, I., Ridenour, C. S., Newman, C., & DeMarco, G. M. P. (2003). A typology of research purposes and its relationship to mixed methods. In A. Tashakkori & C. Teddlie (Eds.), *Handbook of mixed methods in social and behavioral research* (pp. 167-188). Thousand Oaks, CA: Sage.

O'Cathain, A. (2010). Assessing the quality of mixed methods research: Toward a comprehensive framework. In A. Tashakkori & C. Teddlie (Eds.), *SAGE handbook of mixed methods in social and behavioral research* (2nd ed., pp. 531-557). Thousand Oaks, CA: Sage.

Onwuegbuzie, A. J., Bustamante, R. M., & Nelson, J. A. (2010). Mixed Research as a tool for developing quantitative instruments. *Journal of Mixed Methods Research*, *4*, 56-78. doi:10.1177/1558689809355805

Onwuegbuzie, A. J., & Collins, K. M. T. (2007). A typology of mixed methods sampling designs in social science research. *The Qualitative Report*, *12*, 281-316. https://nsuworks.nova.edu/tqr/vol12/iss2/9/

Onwuegbuzie, A. J., & Collins, K. M. T. (2014). The role of Bronfenbrenner's ecological systems theory in enhancing interpretive consistency in mixed research. *International Journal of Research in Education Methodology*, *5*, 651-661.

Onwuegbuzie, A. J., & Collins, K. M. T. (2017). The role of sampling in mixed methods research: Enhancing inference quality. *Koelner Zeitschrift fuer Soziologie und Sozialpsychologie*, *69*, 133-156. doi:10.1007/s11577-017-0455-0

Onwuegbuzie, A. J., & Daniel, L. G. (2005). Editorial: Evidence-based guidelines for publishing articles in Research in the Schools and beyond. *Research in the Schools*,

12(2), 1-11.

Onwuegbuzie, A. J., & Denham, M. A. (2014). Qualitative data analysis techniques. In L. Meyer (Ed.), *Oxford bibliographies in education*. Oxford, UK: Oxford University Press. http://www.oxfordbibliographies.com/view/document/obo-9780199756810/obo-9780199756810-0078.xml

Onwuegbuzie, A. J., & Frels, R. K. (2016). *Seven steps to a comprehensive literature review: A multimodal and cultural approach* (Kindle.). London, England: Sage.

Onwuegbuzie, A. J., & Hitchcock, J. H. (2019). Toward a fully integrated approach to mixed methods research via the $1 + 1 = 1$ integration approach: Mixed Research 2.0. *International Journal of Multiple Research Approaches*, *11*, 7-28. doi:10.29034/ijmra.v11n1editorial1

Onwuegbuzie, A. J., & Johnson, R. B. (2006). The validity issue in mixed research. *Research in the Schools*, *13*(1), 48–63.

Onwuegbuzie, A. J., Johnson, R. B., & Collins, K. M. T. (2011). A framework for assessing legitimation in mixed research. *Quality & Quantity: International Journal of Methodology, 45*, 1253-1271. doi:10.1007/s11135-009-9289-9

Onwuegbuzie, A. J., & Leech, N. L. (2004). Post hoc power: A concept whose time has come. *Understanding Statistics*, *3*, 201-230. doi:10.1207/s15328031us0304_1

Onwuegbuzie, A. J., & Leech, N. L. (2007). A call for qualitative power analyses. *Quality and Quantity*, *41*, 105-121. doi:10.1007/s11135-005-1098-1

Onwuegbuzie, A. J., & Leech, N. L. (2019). On qualitizing. *International Journal of Multiple Research Approaches, 11*, 98-131. doi:10.29034/ijmra.v11n2editorial2

Onwuegbuzie, A. J., Slate, J. R., Leech, N. L., & Collins, K. M. T. (2009). Mixed data analysis: Advanced integration techniques. *International Journal of Multiple Research Approaches*, *3*, 13-33. doi:10.5172/mra.455.3.1.13

Pagano, R. R. (2010). *Understanding statistics* (9th ed.). Belmont, CA: Wadsworth Cengage Learning.

Plano Clark, V. L., & Badiee, M. (2010). Research questions in mixed methods research. In A. Tashakkori & C. Teddlie (Eds.), *SAGE handbook of mixed methods in social and behavioral research* (2nd ed., pp. 275-304). Thousand Oaks, CA: Sage.

Sandelowski, M. (2008). Theoretical saturation. In L. M. Given (Ed.), *The Sage encyclopedia of qualitative methods* (Vol. 1., pp. 875-876). Thousand Oaks, CA: Sage.

Sandelowski, M., Volis, C. I., & Knafl, G. (2009). On quantitizing. *Journal of Mixed Methods Research*, *3*, 208-222. doi:10.1177/1558689809334210

Stake, R. E., & Trumbull, D. J. (1982). Naturalistic generalizations. *Review Journal of Philosophy and Social Science*, *7*, 3-12.

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics* (5th ed.). Boston, MA: Pearson Education.

Tashakkori, A., & Teddlie, C. (1998). *Mixed methodology: Combining qualitative and quantitative approaches*. *Applied Social Research Methods Series* (Vol. 46). Thousand Oaks, CA: Sage.

Tashakkori, A., & Teddlie, C. (2003). The past and future of mixed methods research: From data triangulation to mixed model designs. In A. Tashakkori & C. Teddlie (Eds.), *Handbook of mixed methods in social science and behavioural research* (pp. 671-701). Thousand Oaks, CA: Sage.

Tashakkori, A., & Teddlie, C. (2010a). Epilogue: Current developments and emerging trends in integrated research methodology. In A. Tashakkori & C. Teddlie (Eds.), *SAGE handbook of mixed methods in social and behavioral research* (2nd ed., pp. 803-825). Thousand Oaks, CA: Sage.

Tashakkori, A., & Teddlie, C. (Eds.). (2010b). *Handbook of mixed methods in social and*

behavioral research (2nd ed.). Thousand Oaks, CA: Sage.

Teddlie, C., & Tashakkori, A. (2003). Major issues and controversies in the use of mixed methods in the social and behavioral science. In A. Tashakkori & C. Teddlie (Eds.), *Handbook of mixed methods in social and behavioral research* (pp. 3-50). Thousand Oaks, CA: Sage.

Teddlie, C., & Yu, F. (2007). Mixed methods sampling: A typology with examples. *Journal of Mixed Methods Research*, *1*, 77-100. doi:10.1177/2345678906292430

Wilkinson, L., & Task Force on Statistical Inference. (1999). Statistical methods in psychology journals: Guidelines and explanations. *American Psychologist*, *54*, 594-604. doi:10.1037/0003-066X.54.8.594

Williams, M. (2000). Intepretivism and generalization. *Sociology*, *34*. doi:10.1177/S0038038500000146

Wisdom, J. P., Cavaleri, M. A., Onwuegbuzie, A. J., & Green, C. A. (2012). Methodological reporting in qualitative, quantitative, and mixed methods health services research articles. *Health Services Research*, *47*, 721-745. doi:10.1111/j.1475-6773.2011.01344.x

Yin, R. K. (2009). *Case study research: Design and methods* (Kindle 4th ed.). Thousand Oaks, CA: Sage.

Appendix

Table 1: *Generalization Goals and Accompanying Recommendations for Sample Size/Number of Sampling Units, and Assumptions About the Sample*

Size of Sample	Type of Generalization	Goal of Generalization	Sample Size / Number of Sampling Units Recommendations	Assumptions About Sample	Type of Sampling Strategy
Larger	External (Statistical)	To generalize conclusions to population from the (ideally random) sample	Conduct an *a* priori power analysis (Cohen, 1988) based upon • Desired effect size $(1 - \beta)$ • Desired alpha level (α)	Sample is large and random such that it maximizes its representation of the population from which it was drawn	Mainly random
	Internal (Statistical) • Heterogeneous sample • Homogeneous sample	To generalize conclusions to the sample from the (ideally representative) sub-sample (i.e., key informants)	Heterogeneous: Dependent on variability of sample (i.e., the more heterogeneous the sample, the larger the subset needed; Guest et al., 2006) Homogeneous: $N = 12$ (Guest et al., 2006) $N = 6$ might be sufficient for development of meaningful themes and interpretations	Sub-sample is representative of the study sample	Mainly purposive
	Analytic (Particularistic)	To generalize case study results to some broader theory	E.g., $N = 6\text{-}10$ cases (Yin, 2009)	Sample size is sufficient to achieve data saturation, informational redundancy, and/or theoretical saturation	
Smaller	Case-to-case transfer	To generalize from one case to another (similar) case	E.g., $N = 3\text{-}5$ (Creswell, 2007)	Case to which the generalization is being made is adequately similar in a meaningful way	
Smaller/ Larger	Naturalistic	For the audience reading the study to make generalizations as influenced by their personal, vicarious experiences	$N \geq 1$ (i.e., naturalistic generalizations are made by the audience in all studies, no matter its sample size)	Audience can relate their personal, vicarious experiences to the those of the participants (i.e., sample) in the study	Purposive/ Random
Smaller/ Larger	Moderatum	For the researcher or audience to make modest, pragmatic generalizations drawn from personal experiences	$N \geq 1$ (i.e., moderatum generalizations are made by researchers and the audience in all studies, no matter its sample size)	Researchers or the audience have knowledge of, or can relate to, the participants (i.e., sample) in the study	Purposive/ Random

Table 2. *The Relationship of MMRA to the 13 Steps of the Mixed Research Process and Accompanying Reflexive Questions*

Formulate	

1. Determine the goal of the study	Clearly articulating the goal of your study will later help determine your sampling design, which includes the sampling frame/boundary, sampling combination, sample size, and number of sampling units.
	• What are my *conceptual* (e.g., a-paradigmatic vs. complementary strengths stances) and *philosophical stances* (e.g., pragmatism-of-the-right vs. critical dialectical pluralism)?
	• What is the *goal* of my study (predict; add to the knowledge base; have a personal, social, and/or organizational impact; measure change; understand complex phenomena; test new ideas; generate new ideas; inform constituencies; and, examine the past; Newman, Ridenour, Newman, & DeMarco, 2003)?
	• Based on the goal of the study, what *ecological level of study* (microsystem, mesosystem, exosystem, macrosystem, or chronosystem) is appropriate? (Bronfenbrenner, 1979)
	• Based on the goal of my study and the ecological level of the study, what *generalization goal* (e.g., external, internal, analytic generalization or case-to-case transfer) is appropriate?
	• How do my answers to the above influence my sampling design? Specifically, how do they influence decisions about the
	   o sampling *frame* (probability sampling) or *boundary* (purposive sampling);
	   o *sampling combination* in terms of
	      ▪ mixing dimension (partially or fully mixed),
	      ▪ time dimension (concurrent or sequential),
	      ▪ emphasis dimension (dominant or equal status) and,
	      ▪ relationship among/between samples (identical, parallel, nested, or multilevel);
	   o sample size; and
	   o number of sampling units?

2. Formulate the research objectives	Formulating your research objectives helps to determine the emphasis (dominant or equal status) dimension of the qualitative, quantitative, and/or mixed phase(s) of your research study. It further helps to determine whether you should use a random or purposive sampling scheme (Onwuegbuzie & Collins, 2007).
	• Johnson and Christensen (2010) have identified empirically five mixed research objectives: exploration, description, explanation, prediction, and influence. What is my research objective for the different (i.e., quantitative, qualitative, or mixed) phases of the study?
	• What does my research objective suggest about the following sampling design features?
	   o The use of random versus purposive sampling techniques?
	   o The emphasis dimension (dominant or equal status)?

3. Determine the research/mixing rationale	Collins, Onwuegbuzie, and Sutton (2006) have identified empirically four mixing rationales: • *participant enrichment*: mixing quantitative and qualitative research to optimize the sample using techniques that include recruiting participants, engaging in activities such as institutional review board debriefings, and ensuring that each participant selected is appropriate for inclusion; • *instrument fidelity*: assessing the appropriateness and/or utility of existing instruments, creating new instruments, and monitoring performance of human instruments;

		• *treatment integrity*: assessing the fidelity of an intervention; and • *significance enhancement*: facilitating thickness and richness of data, and augmenting interpretation and usefulness of findings. Knowledge of these four rationales can help researchers to optimize their samples; thus, it is important to reflect on the following: • How do I optimize my sample? • How do I select my sampling design to maximize participant enrichment, instrument fidelity, treatment integrity, and significance enhancement?
4.	Determine the research/mixing purposes	Greene, Caracelli, and Graham (1989) have identified empirically five purposes for mixing methods: • *triangulation* (i.e., seeking convergence and corroboration of findings stemming from different methods [i.e., quantitative and qualitative] studying the same phenomenon); • *complementarity* (i.e., seeking elaboration, enhancement, illustration, clarification of the findings extracted via one method [e.g., qualitative] with results from the other method [e.g., quantitative]); • *development* (i.e., using the findings from one method [e.g., qualitative] to help inform the other method [e.g., quantitative]); • *initiation* (i.e., discovering inconsistencies, paradoxes, and contradictions that lead to a reframing of the research question); and • *expansion* (i.e., seeking to expand the breadth and range of the study by using different methods for different inquiry components). Knowledge of your mixing purpose will help you determine the time dimension (sequential or concurrent) of your sampling design (Onwuegbuzie & Collins, 2007). • What are my research / mixing rationales? • How do my research / mixing rationales help me to determine the time dimension of my sampling design?

5.	Determine the research questions	When writing your research questions, be sure to specify clearly your sampling frame/boundary.
		• Have I specified my sampling frame/boundary in my research questions?
		• Which types of study and sampling design best represent my research questions?
		   o Separate research questions (i.e., one or more quantitative research questions coupled with one or more qualitative research questions)
		   o General overarching mixed methods research questions (i.e., broad questions that are addressed using both quantitative and qualitative approaches)
		   o Hybrid mixed methods issue research questions (i.e., one question with two distinct parts such that a quantitative approach is used to address one part and a qualitative approach is used to address the other part)
		   o Mixed methods procedural/mixing research questions (i.e., narrow questions that direct the integration of the qualitative and quantitative strands of the study)
		   o Combination research questions (i.e., at least one mixed methods question combined with separate quantitative and qualitative questions)
		   o Independent research questions (i.e., questions that are related, with each question not depending on the results of the other question[s])
		   o Dependent research questions (i.e., questions that depend on the results stemming from addressing another question)
		   o Predetermined research questions (i.e., questions based on literature, practice, personal tendencies, and/or disciplinary considerations that are posed at the beginning of the study)
		   o Emergent research questions (i.e., new or modified research questions that arise during the design, data collection, data analysis, or interpretation

		phase) • How do my research questions help me to determine the emphasis (dominant or equal status) of my study?
Plan		
6.	Select the sampling design	When selecting the sampling design, consider the following four steps: (1) setting the sampling frame/boundary, (2) selecting the sampling combination, (3) selecting the sampling size, and (4) selecting the number of sampling units. • What is my sampling frame/boundary? • What is my sampling combination in terms of the mixing dimension (partially or fully mixed), time dimension (concurrent or sequential), emphasis dimension (dominant or equal status), and the relationship between/among the samples (identical, parallel, nested, or multilevel)? • What sample size and how many sampling units do I need to achieve statistical power and/or saturation? • To what extent does my sampling design align with the decisions I have made, and will make, throughout the mixed research process?

7.	Select the mixed methods research design	Knowledge of the research design helps to frame/bound the study with respect to the sampling design. Nastasi, Hitchcock, and Brown (2010) provide a six-element inclusive framework for conceptualizing mixed research design typologies:
		   o Single versus multiple phases
		   o Types of data used, the manner in which they are mixed, and priority/dominance of QUAL or QUANT in the study design
		   o Stage of the research process at which mixing occur
		   o Integrated typologies (or level of integration)
		   o Iterative
		   o Synergistic
		• To what extent is my sampling design consistent with my research design?

Implement		

8.	Collect the data	Throughout data collection process, reflect on the sampling boundary/parameters and whether further sampling needs to occur to achieve greater power/saturation. Plan for over-sampling.
		• To what degree have I oversampled in case of participant attrition and/or non-response?
		• To what extent are the data that I have collected sufficient to achieve representation? Your sample size should permit you to reach a reasonable saturation/representation trade-off (Teddlie & Yu, 2007).
		Teddlie and Tashakkori (2009) conceptualized a 36-element typology of mixed data collection strategies, comprising the following:
		   o 30 between-strategies mixed data collection combinations (e.g., quantitative observations with qualitative-based focus group); and
		   o 6 within-strategies mixed data collection combinations (e.g., quantitative interview and qualitative interview)
		• To what degree does my sampling frame/boundary allow me to conduct my selected between -strategies and/or within-strategies mixed data collection combinations?

9.	Analyze the data	When analyzing data, be sure to choose analyses that are appropriate for your sample size(s). • To what extent are the analyses that I make appropriate for my sampling frame/boundary, sampling combination, sample size, and number of sampling units? • To what extent does my sampling frame/boundary, sampling combination, sample size, and number of sampling units yield data for which the quantitative assumptions (e.g., population assumptions, sampling assumptions, distributional

	assumptions [e.g., general linear model assumptions, structural assumptions, cross-variation assumptions]) and qualitative assumptions (e.g., data saturation, theoretical saturation, information redundancy) are met?
10. Legitimate the data	Onwuegbuzie and Johnson (2006) conceptualize legitimation with regards to sampling, referred to as *integration legitimation*, which represents "[t]he extent to which the relationship between the quantitative and qualitative sampling designs yields quality meta-inferences" (p. 57). • To what extent have I achieved sample integration legitimation?
11. Interpret the data	Interpreting the data involves making inferences and reporting their significance. In tandem with reporting the significance of inferences, it is important to also report assurances of the quality standards used when making these inferences; otherwise, it can be difficult for the audience to ascertain the validity/trustworthiness of your findings. Teddlie and Tashakkori (2009) provide an interpretive framework for inference quality, which speaks in part to justifying one's sampling design. Reflect on the following four aspects of their inference quality framework that are pertinent to sampling: • Design suitability (e.g., To what extent is my sampling design appropriate for answering my research questions? To what extent does my sampling design allow me to achieve representativeness [i.e., the appropriate balance of power and saturation?]) • Design fidelity (e.g., To what extent are the qualitative, quantitative, and mixed methods sampling designs suitable for capturing the meanings, effects, or relationships being investigated in my study?) • Within-design consistency (e.g., To what extent does my sampling design allow for interpretive consistency? In other words, to what extent are my generalizations warranted, given the sampling design? To what extent do the components of my study—from my research questions, to the sampling design, to the inferences that I report—align in a seamless manner?) • Analytic adequacy (e.g., To what extent are my data analyses appropriate given my sampling design? To what extent have I selected an appropriate sample that will provide me with the rich analyses that I need to answer my research question?) When interpreting the data, use MMRA to draw appropriate meta-inferences. • To what extent have I used MMRA in order to draw appropriate meta-inferences? • To what extent are my generalizations appropriate given my MMRA?
Disseminate the Results	
12. Write the research report	When writing the research report, justify how your generalizations are appropriate given the results of your MMRA. • To what extent do I report why my generalizations are justified based on my MMRA? • To what extent did I remember to report my sampling frame/boundary, sampling design, all effect sizes, and whether or not my data achieved representation?
13. Reformulate the research questions	Upon completing the study, a new study begins with a reformulation of the research questions. • How could this study be conducted with a different sample or sampling design to enhance one or more of the generalization goals?

Table 3. *Major Sampling Schemes in Mixed Methods Research*

Sampling Scheme	Description
Random Sampling:	
Simple	Every individual in the sampling frame (i.e., desired population) has an equal and independent chance of being chosen for the study.
Stratified	Sampling frame is divided into sub-sections comprising groups that are relatively homogeneous with respect to one or more characteristics and a random sample from each stratum is selected.
Cluster	Selecting intact groups representing clusters of individuals rather than choosing individuals one at a time.
Systematic	Choosing individuals from a list by selecting every *kth* sampling frame member, where *k* typifies the population divided by the preferred sample size.
Multi-Stage Random	Choosing a sample from the random sampling schemes in multiple stages.
Purposive Sampling:	
Convenience	Choosing settings, groups, and/or individuals that are conveniently available and willing to participate in the study.
Maximum Variation	Choosing settings, groups, and/or individuals to maximize the range of perspectives investigated in the study.
Homogeneous	Choosing settings, groups, and/or individuals based on similar or specific characteristics.
Criterion	Choosing settings, groups, and/or individuals because they represent one or more criteria.
Typical	Selecting and analyzing average or normal cases.

Intensity	Choosing settings, groups, and/or individuals because their experiences relative to the phenomena of interest are viewed as intense but not extreme.
Critical Case	Choosing settings, groups, and/or individuals based on specific characteristic(s) because their inclusion provides researcher with compelling insight about a phenomenon of interest.
Extreme Case	Selecting outlying cases and conducting comparative analyses.
Quota	Researcher identifies desired characteristics and quotas of sample members to be included in the study.
Theory-Based	Choosing settings, groups, and/or individuals because their inclusion helps the researcher to develop a theory.
Confirming/ Disconfirming	After beginning data collection, researcher conducts subsequent analyses to verify or to contradict initial results.
Snowball/Network/Chain	Participants are asked to recruit individuals to join the study.
Opportunistic	Researcher selects a case based on specific characteristics (i.e., typical, negative, or extreme) to capitalize on developing events occurring during data collection.
Politically Important Case	Choosing settings, groups, and/or individuals to be included or excluded based on their political connection to the phenomena of interest.
Random Purposeful	Selecting random cases from the sampling frame and randomly choosing a desired number of individuals to participate in the study.
Stratified Purposeful	Sampling frame is divided into strata to obtain relatively homogeneous sub-groups and a purposeful sample is selected from each strata.
Mixed Purposeful	Choosing more than one sampling strategy and comparing the results emerging from both samples.
Multi-Stage Purposeful Random	Choosing settings, groups, and/or individuals representing a sample in two or more stages. The first stage is random selection and the following stages are purposive selection of participants.
Multi-Stage Purposeful	Choosing settings, groups, and/or individuals representing a sample in two or more stages in which all stages reflect purposive sampling of participants.

Table 4: *Minimum Sample Size Recommendations for Selected Qualitative and Quantitative Research Designs*

Research Design/Method	Minimum Sample Size Suggestion
Research Design	
Correlational	64 participants for one-tailed hypotheses; 82 participants for two-tailed hypotheses (Onwuegbuzie, Jiao, & Bostick, 2004)
Causal-Comparative	51 participants per group for one-tailed hypotheses; 64 participants for two-tailed hypotheses (Onwuegbuzie et al., 2004)
Experimental	21 participants per group for one-tailed hypotheses (Onwuegbuzie et al., 2004)
Case Study	4-5 participants (Creswell, 2013)
Phenomenological	3-10 (Dukes, 1984); ≥ 6 (Morse, 1994); 5 to 25 (Polkinghorne, 1989)
Grounded Theory	20-30 (Creswell, 2013)
Ethnography	1 cultural group (Creswell, 2002); 30-50 interviews (Morse, 1994)
Ethological	100-200 units of observation (Morse, 1994)
Narrative	1-2 (Creswell, 2013); > 2 to develop a collective story
Sampling Design	
Subgroup Sampling Design	≥ 3 participants per subgroup (Onwuegbuzie & Leech, 2007)
Nested Sampling Design	≥ 3 participants per subgroup (Onwuegbuzie & Leech, 2007)
Research Method	
Interviews	6 interviews may be "sufficient to enable development of meaningful themes and useful interpretations" (Guest, Bunce, & Johnson, 2006, p. 78)

12 interviews are sufficient to "understand common perceptions and experiences among a group of relatively homogeneous individuals" (Guest et al., 2006, p. 79)

23-37 interviews [the mean number of participants interviewed in PhD studies, depending on research approach (e.g., action research 23, life history 23, content analysis 25, discourse analysis 25, phenomenology 25, ethnomethodology 31, grounded theory 32, ethnography of communication 34, critical/emancipatory research 35, case study 36, ethnographic content analysis 37; Mason, 2010)]

8 or 16 in-depth interviews (the median number of interviews required to reach 80% and 90% saturation, respectively; Namey, Guest, McKenna, & Chen, 2016)

Focus Group

6-9 participants (Krueger, 2000); 6-10 participants (Langford, Schoenfeld, & Izzo, 2002; Morgan, 1997); 6-12 participants (Johnson & Christensen, 2013); 6-12 participants (Bernard, 1995); 8–12 participants (Baumgartner, Strong, & Hensley, 2002)

3 or 5 focus groups (the median number of focus groups required to reach 80% and 90% saturation, respectively; Namey, Guest, McKenna, & Chen, 2016)

2-3 focus groups (more than 80% of all themes were discoverable); 3-6 focus groups (90% of all themes were discoverable; 3 focus groups (enough to identify all of the most prevalent themes within the data set; Guest, Namey, & McKenna, 2016)

3 (Morgan, 1997) to 4 (Krueger, 1994) participants yield "mini-focus groups" (Krueger, 1994, p. 17)

3-6 focus groups should be formed (Krueger, 1994; Morgan, 1997) to assess data and/or theoretical saturation

Adapted from Onwuegbuzie, A. J., & Collins, K. M. T. (2007). A typology of mixed methods sampling designs in social science research. *The Qualitative Report, 12*, 281-316. Retrieved from http://www.nova.edu/ssss/QR/QR12-2/onwuegbuzie2.pdf

Figure 1. **A Meta-Framework for Mixed Methods Representation Analyses**
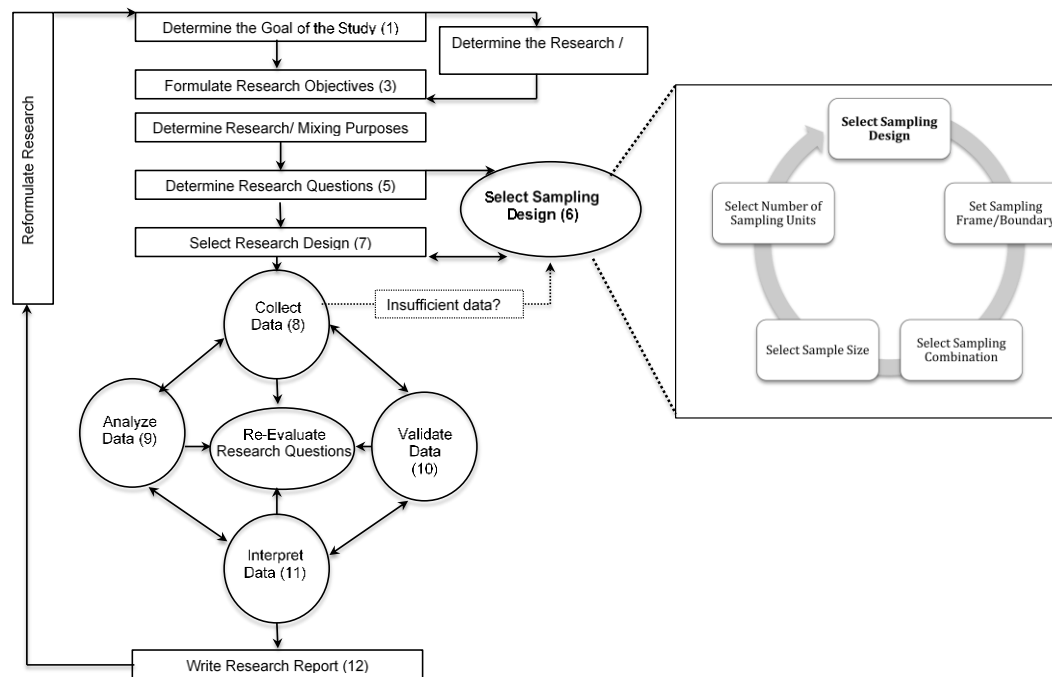
Author Note

Julie A. Corrigan is an Assistant Professor at Concordia University in Montreal where she teaches courses in educational technology and methodology. Correspondence regarding this article can be addressed directly to: Julie.Corrigan@concordia.ca

Anthony J. Onwuegbuzie is a Senior Research Associate at the University of Cambridge. Further, he is a Distinguished Visiting Professor at the University of Johannesburg; Honorary Professor at the University of South Africa; Visiting Senior Scholar, St. John's University, New York; and an Honorary Recognised Supervisor (Online), University of Liverpool. As immediate Past President of the Mixed Methods International Research Association (MMIRA), and as someone who is passionate about qualitative research, quantitative research, and mixed research, Tony co-authored the SAGE mixed research textbook with Rebecca Frels (Lamar University), entitled, *Seven Steps to a Comprehensive Literature Review: A Multimodal and Cultural Approach*. He is former editor of *Educational Researcher*. Currently, he is editor-in-chief of the *International Journal of Multiple Research Approaches* and co-editor of *Research in the Schools*. Correspondence regarding this article can also be addressed directly to: tonyonwuegbuzie@aol.com.

Copyright 2020: Julie A. Corrigan, Anthony J. Onwuegbuzie, and Nova Southeastern University.

Article Citation

Corrigan, J. A., & Onwuegbuzie, A. J. (2020). Toward a meta-framework for conducting mixed methods representation analyses to optimize meta-inferences. *The Qualitative Report, 25*(3), 785-812. https://nsuworks.nova.edu/tqr/vol25/iss3/15